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A new method for reconstructing past-climate trends using tree-ring data and kernel smoothing

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ABSTRACT

Mediterranean high-relief karst areas are very vulnerable to changes in temporal patterns of precipitation and temperature. Understanding climate change in these areas requires current climate trends to be assessed within the context of the variability of rainfall and temperature trends in the recent past. A major difficulty is that the instrumental record in these high-relief areas is very limited and the use of data from paleoclimatic proxies, such as tree-ring data, is required to infer past climate variability. Furthermore, for complex relationships between tree-ring data and climatic variables, it is almost impossible to infer past inter-annual variations in temperature or precipitation, and the inference is limited to the reconstruction of low-frequency variability (i.e., the trend). To do so, in this work, we propose a new method based on detecting trends (by kernel smoothing) in tree variables that show maximum correlation with the trends (also estimated by kernel smoothing) of climate variables. This enables a standard regression framework to be established to reconstruct past climate. We have used tree-ring proxy data from *Abies pinsapo* to evaluate past climate trends in the Sierra de las Nieves karst massif in Southern Spain. Our analysis has found that during the last three hundred years the smoothed mean annual rainfall steadily decreased until the beginning of the 20th century and thereafter it remained more or less constant until the end of the century. On the other hand, the smoothed mean annual temperature has steadily increased since the beginning of the 18th century until recent times. These trends are also suggested by the climate projections for the latter part of the current 21st century. As the study area is a high-relief karst massif of significant hydrologic and ecologic interest, the implications of these trends should be taken into account when formulating effective action plans to mitigate the impact of climate change.

1. Introduction

Climate change affects the biodiversity and geodiversity of many vulnerable areas. This is especially so in areas of high-relief Mediterranean karst massifs where very specific present-day ecosystems have been established by adapting to local climate variables at high elevation (Lindner et al., 2010; Loáiciga et al., 2000). Present-day ecosystems are the result not only of current conditions but also of past climate. In this context, the analysis of historical climate data, especially those of the recent past (i.e., last few centuries), provides a better understanding of current climate change and its effects. Thus, the reconstruction of past climates is of paramount importance because it allows the current precipitation and temperature trends to be placed in historical perspective. Is the 20th century warming abrupt and exceptional? This question can only be answered by taking into account of the magnitude of past climate variability. In addition, the association of forcing factors with past climate change helps us to understand why climate changes and the types of change that can be expected in the near future. Again, to do so requires an assessment of past climate variability.

There have always been fluctuations in climate and it is of particular interest to assess local climate variability in terms of rainfall and temperature. However, past instrumental meteorological data are scarce, especially in these high-altitude areas; instrumental measurements of climate variables, such as rainfall and temperature, are usually limited to meteorological stations in towns in the nearby valleys. In these cases,

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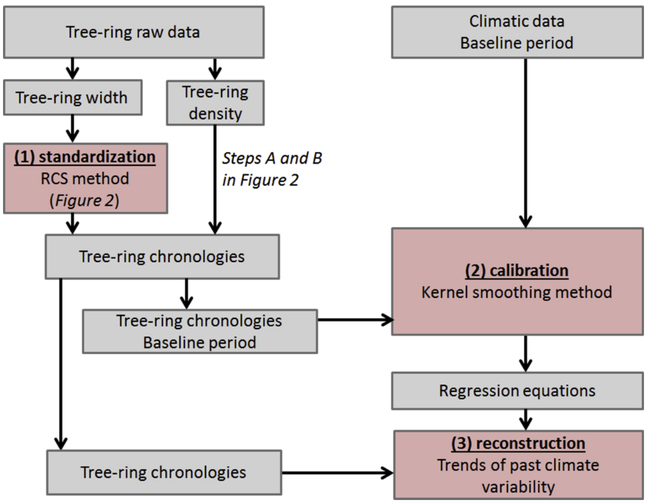


Fig. 1. Workflow for the proposed methodology. Tree-ring raw data (width and density) are available for a long period. Some of this period overlaps the climate data for the so-called baseline period and the inference of past climate is done for the time with tree-ring data before the baseline period. The first step is to obtain the tree-ring chronologies that will require standardisation of the tree-ring width variables (as explained in the main text). The second step is calibration in order to infer a regression relationship between trends of tree-ring variables and climate variables that will be used in the third step of reconstruction to infer past climate variability in the trends.

other climate proxies must be used to reconstruct past climate variability. Among the available climate proxies, assuming that a yearly resolution is adequate, the most suitable method is the use of tree rings (i.e., Schweingruber, 1987; Speer, 2010; Stoffel et al., 2010; Wimmer and Vetter, 1999). Rainfall, as a measure of water availability, and temperature, are two climate variables that significantly affect tree growth features (i.e., Źywiec et al., 2017). Thus, tree-ring parameters can be used as a valuable proxy to obtain information on past rainfall and temperature (Cook and Kairiukstis, 1989). In general, the most commonly used tree-ring parameters are the tree-ring widths and densitometric measurements (Grudd, 2008; Kirdyanov et al., 2008). Three steps are required to use these two variables in paleoclimate reconstruction: (1) standardization of the tree-ring measurements, (2) calibration of standardized tree-ring measurements against instrumental records and (3) using a statistical procedure (e.g., statistical regression) to conduct the reconstruction.

Measurements of all variables include noise originating from various sources including other environmental variables that affect growth (e.g., availability of light, competition with neighbouring trees, soil nutrients, forest fires, insect attacks). Additionally, some tree-ring variables, such as tree-ring width, are affected by a growth trend in the tree and must be standardized (Fritts, 1976; Cook and Kairiukstis, 1989). This systematic change can be modelled and removed from the original time series to provide a variable that changes only with environmental factors. One of several detrending methods is used depending on the form of the trend in the growth of the tree. Usually, there is a declining growth trend in normally growing trees that can be approximated by a negative exponential curve (Helama et al., 2016). Other tree-ring variables, such as density, do not need this standardization.

In the second step, the correlation between the chronology and the instrumental climate data is used to find a statistical relationship that can be used to transform tree-ring data into estimates of paleoclimate data. However, this classical framework of dendroclimatological analysis may be complicated when the relationship between the tree-ring variables and the paleoclimate records is complex and far from a simple linear relationship for which paleoclimate data can be reconstructed from standard regression techniques. In this work we present an application of statistical techniques to reconstruct past climate variability based on finding the trends in the tree variables that have the maximum correlation with the trends in the climate variables and then establishing a standard regression framework.

2. Methodology

The most common tree-ring variables used for extracting paleoclimatic information are tree-ring width series (early wood tree-ring width, late wood tree-ring width and total tree-ring width) and ring density series (minimum tree-ring wood density, maximum tree ring wood density and mean tree ring wood density) (Büntgen et al., 2010; Esper et al., 2015; Fritts, 1976; Grudd, 2008).

The workflow of the methodology is given in Fig. 1, in which there are three main step-wise problems to be solved: (1) standardisation (Helama et al., 2004), (2) calibration and (3) reconstruction (Fritts et al., 1971). Standardisation is required because some tree-ring variables, such as tree ring width variables, have a biological trend (i.e., an ageing trend in tree growth which is independent of climate) that must be removed (Bontemps and Esper, 2011). The most commonly used standardisation method is Regional Curve Standardisation (RCS) (Briffa et al., 1992) because it has the ability to preserve low frequency (i.e., generally multi-centennial) climatic fluctuations (Helama et al., 2016). The RCS method has been reported to retain more low-frequency signal than methods based on individual tree detrending (Melvin and Briffa, 2008). Although other methods are available (e.g., cubic smoothing splines (SPL) which model the high frequency variation better), the RCS standardisation tracks the low-frequency trends more robustly (Wilson et al., 2005). In other cases, more sophisticated statistical modelling provides similar long-term chronologies as the RCS method (Bontents and Esper, 2011). For all these reasons, we have used the RCS method in this work to standardise tree-ring width variables.

For a given study area, a number of radial tree-ring series (raw or original time series) are obtained from the same or different trees and these are used to determine the width and density variables. For each width variable, the RCS method comprises the following steps (Fig. 2):

i) Align the raw series of a site by biological year (starting at year 1). This step A in Fig. 2. The biological year, or cambial age, is the ring number from the pith (Spicer and Gartner, 2001). The raw time series of the variable aligned by biological year are denoted by:

$$\{v_{ik};\ i = 1, \ldots, n_k;\ k = 1, \ldots, N\} \tag{1}$$

n_k: number of tree-rings of the k-thm series.

N: total number of tree-ring series at the same site from the same or different trees. Note that because no all the series have the same number of tree-rings each series has its own length and for each biological year there may be a different number of series n_{ik}.

- Compute the mean series $\{\bar{v}_i,\ i = 1,\ \ldots, n_{max}\}$. This is step B in Fig. 2.

$$\bar{v}_i = \frac{1}{m_i} \sum_{k=1}^{m_i} v_{ik} \tag{2}$$

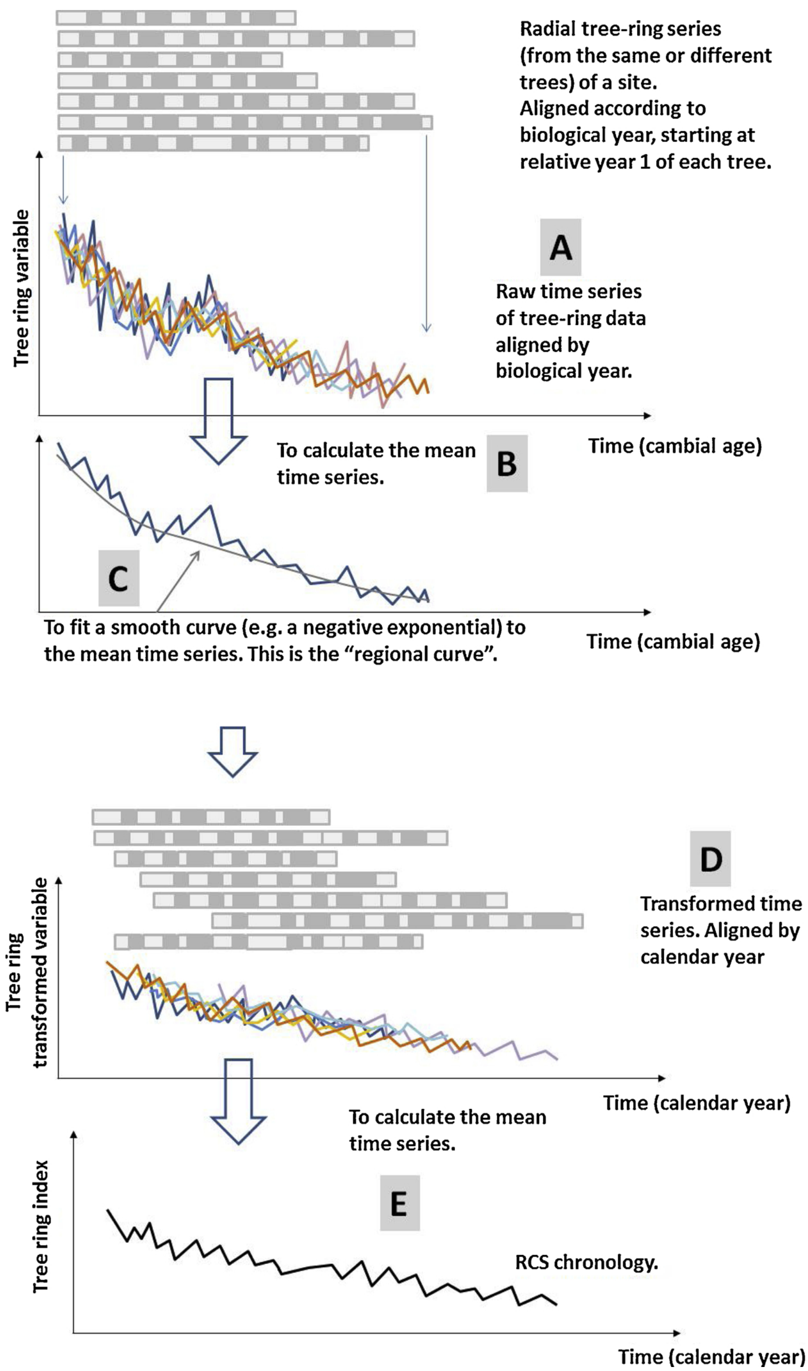


Fig. 2. Steps for calculating the RCS chronology of a site. A. The radial raw tree ring series are aligned by biological year. B. The mean time series is calculated from the aligned time series. C. A negative exponential is fitted to the mean time series to obtain the RCS curve. D. Each raw time series is divided by the RCS curve to obtain the transformed time series. The transformed time series are aligned. E. The mean of the transformed time series is calculated, and this constitutes the final RCS chronology.

Where m_i is the number of times series for the i-thm biological year.

- Fit a smooth mathematical function, to the mean time series to obtain the so-called regional curve (RC); this is step C in Fig. 2. For example, a negative exponential curve:

$$\tilde{v}_i = \beta e^{-\alpha i} \tag{3}$$

where α and β are the parameters obtained by a least squares fitting of the equation to the mean time series $\{\bar{v}_i,\ i = 1,\ \ldots, n_{max}\}$.

- Divide each raw time series by the RC curve values. This is a standardisation to obtain the time series of tree-ring index

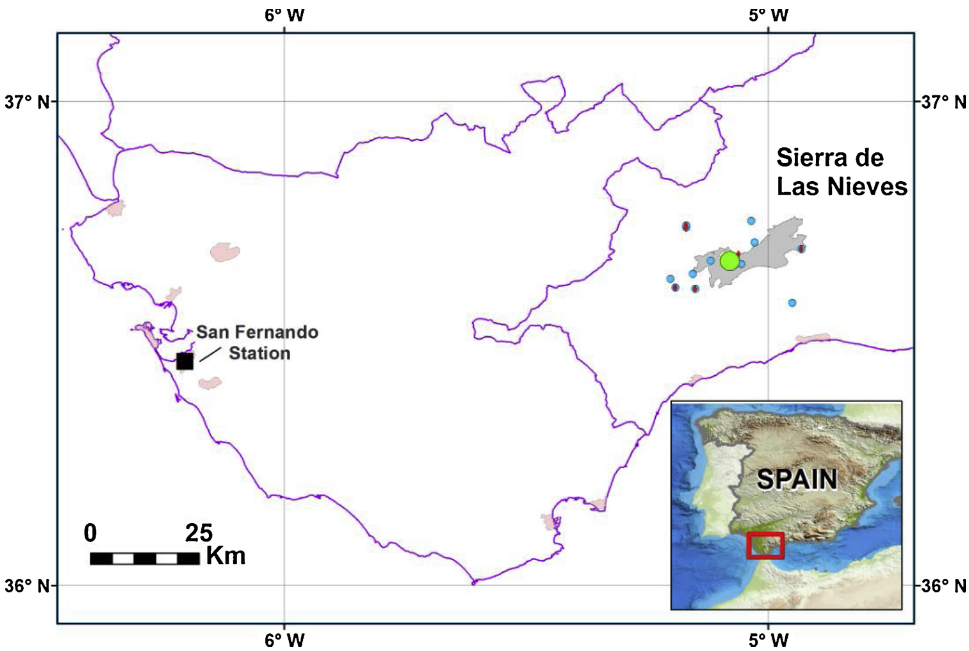


Fig. 3. Location of the study area in the Sierra de las Nieves karst aquifer (southern Spain) and location of the San Fernando station. The green point represents the location of *Abies pinsapo* series used in this research and the other points around it represent the locations of local meteorological stations (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

$$I_{ik} = \frac{v_{ik}}{\tilde{v}_i}\,;\ i = 1,\ \ldots, n_k;\ k = 1,\ \ldots,\ N \tag{4}$$

- Return the time series of tree-ring index to the calendar year. These are called the transformed series. This step D in Fig. 2.
- Calculate the mean of the transformed series, called the RCS site chronology (step E in Fig. 2):

$$\bar{I}_j = \frac{1}{l_j}\sum_{k=1}^{l_j} I_{jk} \tag{5}$$

where l_j is the number of time series for the calendar year j.

When dealing with tree-ring density variables, the raw chronologies are obtained by applying Eq. (5) to the raw variables as the biological growth trend is not present in these variables.

The second step-wise problem is calibration. In this second step, RCS chronologies (or raw chronologies for ring-density variables) must be correlated with instrumental rainfall and temperature data (Fritts, 1976; Esper et al., 2002). This step is easily solved, by standard statistical regression, if there is a high correlation (for example, an absolute value of correlation larger than 0.8) between the tree-ring variable and the instrumental climatological variable (temperature or precipitation). However, in many cases the relationship between the variables is complex and is not clear from simple regression graphs. This may be because the noise in the tree-ring chronologies hide the climatic signal. Thus, rather than trying to reconstruct precise values of past rainfall and temperature it is more appropriate to evaluate long-term trends (i.e. low frequency variation) in the past variability of rainfall and temperature. One possible approach is to smooth the time series of both tree-ring variables and climate variables using a moving window smoother with the bandwidth chosen to maximise the correlation between the smoothed time series of tree-ring chronologies and climate variables. One form of kernel smoothing (Ghosh, 2018) for trend estimation is the simple moving average (SMA). Given a time series of n data $\{\bar{I}_1,\ \bar{I}_2,\ldots,\bar{I}_n\}$ the trend is the new time series $\{T_1,\ T_2,\ldots,T_n\}$ in which each value is calculated from the original series by the SMA with a bandwidth of M values defined as:

$$\bar{T}_j = \frac{\bar{I}_{j-M/2} + \bar{I}_{j-\frac{M}{2}+1} + \ldots + \bar{I}_{j+\frac{M}{2}-1} + \bar{I}_{j+M/2}}{M+1}$$

A statistical relationship between tree-ring variables and climate variables is established from the smoothed time series (or trend), and the smoothed times series of rainfall and of temperature can be reconstructed together with their variability by standard linear regression:

$$\bar{C}_j = \alpha + \beta\bar{T}_j$$

Where $\bar{C}_j$ is the reconstructed trend of the climate variable (rainfall or temperature) for year j based on the trend of the tree-ring variable $\bar{T}_j$. α and β are the regression coefficients estimated in the calibration step.

3. Case study

The study area is the Sierra de las Nieves karst massif in the province of Málaga, Southern Spain (Fig. 3). This is a high-relief karst area of significant hydrological and ecological value that is likely to be very vulnerable to climate change (Pardo-Igúzquiza et al., 2015). The area is a Natural Park and, since 1995, a UNESCO Biosphere Reserve. There are no instrumental meteorological records in the vicinity of this area that are longer than a few decades (Pardo-Igúzquiza et al., 2012). Thus, proxy data must be used for past climate reconstructions. In particular, there are public domain tree-ring data obtained for a larger study of the entire Iberian Peninsula (Braker and Schweingruber, 1984). The data are used by the second author in Briffa et al. (1988) as part of a network across Europe used to reconstruct summer temperature patterns for the period 1750–1800 using maximum latewood density chronologies of coniferous trees. The results of Briffa et al. (1988) are synoptic for

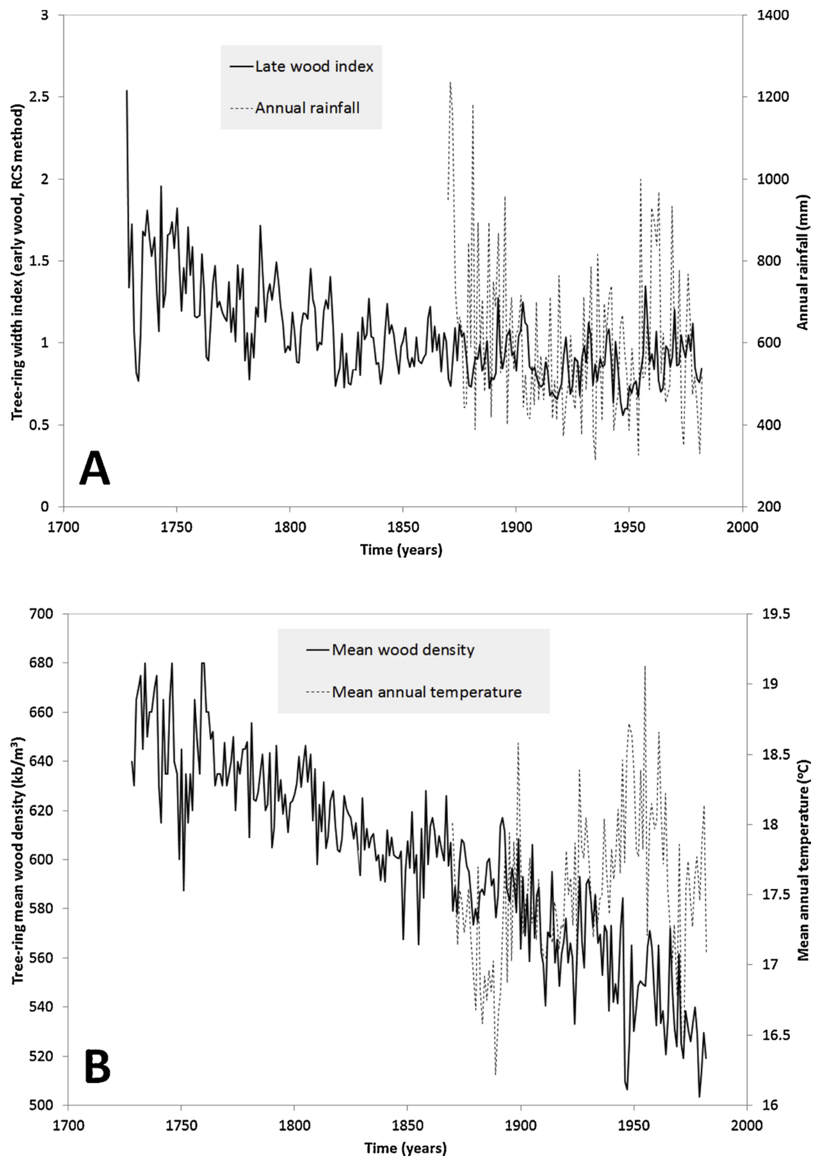


Fig. 4. A: Time series of RCS index of early wood tree-ring width and annual rainfall at San Fernando station. B: Raw mean tree-ring wood density and mean annual temperature at San Fernando station.

Table 1
Correlation coefficients between the tree-ring variables and the climate variables.

	Rainfall year	Rainfall winter	Rainfall spring	Rainfall summer	Rainfall autumn	Temp. year	Temp. winter	Temp. spring	Temp. summer	Temp. autumn
EARLY WOOD WIDTH	0.03	−0.07	−0.1	0.17	0.04	−0.07	0.01	0.01	−0.06	−0.11
LATE WOOD WIDTH	0.05	0.06	−0.1	0.12	0.17	0.18	0.21	0.22	0.06	0.05
ANNUAL WOOD WIDTH	0.02	−0.03	−0.14	0.18	0.08	0.05	0.12	0.12	0	−0.03
MINIMUM WOOD DENSITY	−0.01	−0.06	0.07	−0.23	0.05	0	−0.14	0.04	0.05	−0.01
MAXIMUM WOOD DENSITY	0.07	−0.14	0.06	0.09	0.16	−0.22	−0.22	−0.04	−0.16	−0.18
MEAN WOOD DENSITY	0.06	−0.14	0.07	0.04	0.16	−0.21	−0.24	−0.03	−0.15	−0.18

Table 2
A: Maximum correlation coefficient between the smoothed tree-ring variables and the smoothed climate variables. B: Values of the semi-bandwidth (in years) for which the maximum correlation between the smoothed series is reached.

A

	Rainfall year	Rainfall winter	Rainfall spring	Rainfall summer	Rainfall autumn	Temp. year	Temp. winter	Temp. spring	Temp. summer	Temp. autumn
EARLY WOOD WIDTH	0.93	0.69	0.83	−0.59	0.81	−0.75	−0.69	−0.74	−0.95	−0.79
LATE WOOD WIDTH	−0.78	0.73	−0.89	0.85	−0.88	0.91	0.94	0.92	0.88	0.89
ANNUAL WOOD WIDTH	−0.69	0.86	−0.81	0.82	−0.79	0.83	0.87	0.83	0.79	0.8
MINIMUM WOOD DENSITY	0.9	−0.44	0.97	−0.95	0.96	−0.96	−0.99	−0.95	−0.93	−0.95
MAXIMUM WOOD DENSITY	0.91	−0.46	0.98	−0.9	0.97	−0.98	−1	−0.97	−0.95	−0.96
MEAN WOOD DENSITY	0.91	−0.46	0.98	−0.91	0.97	−0.98	−1	−0.97	−0.95	−0.96

B

	Rainfall year	Rainfall winter	Rainfall spring	Rainfall summer	Rainfall autumn	Temp. year	Temp. winter	Temp. spring	Temp. summer	Temp. autumn
EARLY WOOD WIDTH	38	80	34	35	38	65	38	65	80	33
LATE WOOD WIDTH	54	34	54	53	49	49	49	44	50	54
ANNUAL WOOD WIDTH	54	35	49	53	49	49	49	48	48	49
MINIMUM WOOD DENSITY	55	42	46	68	50	46	75	41	46	46
MAXIMUM WOOD DENSITY	54	44	56	80	48	46	57	42	46	51
MEAN WOOD DENSITY	54	44	56	80	48	44	41	42	44	49

Europe and they are not comparable with the results of the present study where we focus on climate variability on a local scale. This is needed in the Sierra de las Nieves in order to understand past climate change and variability which will help understand the current trends and will allow the park environmental managers to plan actions against the impact of possible climate change on the water resources and the biodiversity of the Sierra de las Nieves Natural Park.

The original data (including both raw tree-ring widths and raw tree-ring wood density data) are available from the International Tree-Ring Data Bank and the National Oceanic and Atmospheric Administration. The series of tree-ring data are from *Abies pinsapo* at an altitude of 1650 m (Braker and Schweingruber, 1984). *Abies pinsapo* is a circum-Mediterranean tree that is found only in the mountain ranges of Southern Iberia and Northern Morocco (Linares and Carreira, 2009; Linares et al., 2009; Quézel et al., 1999). *Abies pinsapo* has a limited area of distribution at five sites, three in southern Spain and two in the north of Morocco (Esteban et al., 2010). The sites in Spain are located in the Serranía de Ronda, which is in the high mountain ranges of the westernmost part of the Betic Cordillera, and they span the provinces of Málaga and Cádiz (Fernández-Cancio et al., 2007; Esteban et al., 2010). *Abies pinsapo* occurs in hyper-wet Mediterranean climates, with an annual precipitation between 1000 and 3000 mm, but with a dry summer season from June to September (Fernández-Cancio et al., 2007) and it is adequate for dendroclimatology studies (Génova, 2007).

There are six tree-ring proxies available in the study area. Three proxies are tree-ring width variables (early wood width index, late wood width index and total width index) and the other three are ring-density variables (minimum, maximum and mean tree-ring wood density). The RCS methodology was applied to the tree-ring width variables to obtain the RCS chronologies. The raw chronologies were used for the density variables. As an example, Fig. 4 shows the chronologies of early wood width index (Fig. 4A) and mean wood density (Fig. 4B). The chronologies were obtained using a number of series that range from one (for the first 21 years) to 22. As the instrumental record in the area is very short (covering only the last few decades), the longest time series, San Fernando (Fig. 4), was chosen even though this meteorological station is 100 km to the west of the tree-ring data location and with an elevation close to sea level. Nevertheless, the San Fernando annual time series for rainfall and temperature are well correlated with the mean time series calculated from the stations around Sierra de las Nieves. Both locations belong to the same climatic area and the altitudinal differences imply more rainfall and lower temperature because of the increase in altitude from sea level to the height of the Sierra de las Nieves. However, the trends are the same for the regional area that comprises both locations.

For the San Fernando station there are continuous monthly and annual records of rainfall and temperature from 1870 to the present. Ten climatic variables were processed: total annual rainfall, spring rainfall, summer rainfall, autumn rainfall, winter rainfall, mean annual temperature, mean spring temperature, mean summer temperature, mean autumn temperature and mean winter temperature. The period from 1870 to 1982 was used for calibration purposes; there are no tree-ring data available after 1982.

The calibration data are chosen to cover the time span in which the tree-ring data and the instrumental data overlap. As there are six tree-ring variables and ten climate variables, there are 60 possible combinations (pairs) of tree-ring variables and climate variables. Fig. 4 shows two of those combinations. Fig. 4A shows the relationship between the early wood width index and yearly rainfall and Fig. 4B shows the relationship between mean wood density and mean annual temperature. The relationships in Fig. 4 are complex and there is no simple correlation between the time series. In fact, the linear correlation between the tree-ring variables and the climate variables is negligible as can be seen in Table 1. Detecting any relationship requires a robust procedure, in the sense of finding statistical relationships between means (i.e., trends or low-frequency variability) rather than between the actual data

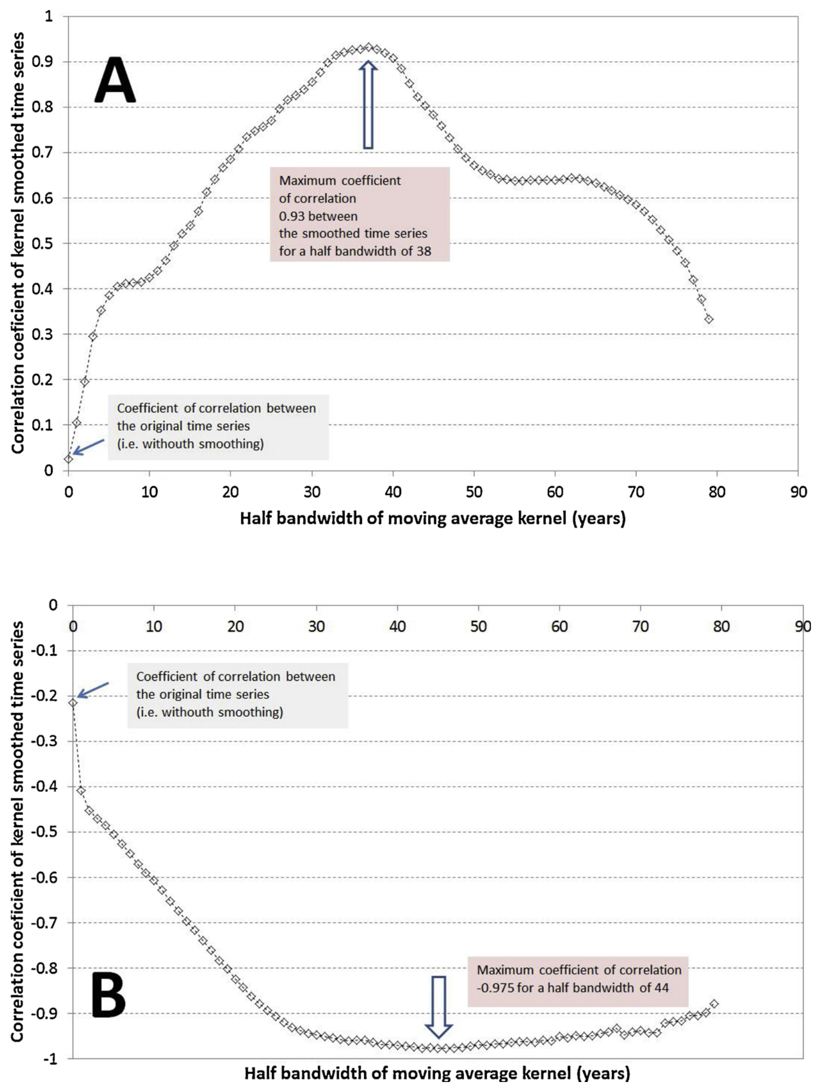


Fig. 5. Reconstruction of rainfall. A: Correlation coefficient between the smoothed early wood tree-ring width and smoothed yearly rainfall as a function of the semi-bandwidth that defines the amount of smoothing. B: Correlation coefficient between the smoothed mean tree-ring wood density and smoothed yearly mean temperature as a function of the semi-bandwidth that defines the amount of smoothing.

as in Fig. 4. This can be done by using a moving window running mean applied to every series used in the calibration period, as described in the methodology section. In this smoothing, the bandwidth is selected so as to maximise the correlation between each tree-ring variable and each climate variable for the calibration period of 1870-1982. The maximum correlation coefficients are given in Table 2A and the optimal semi-bandwidth for rainfall is given in Table 2B. It can be seen that, in most cases, very high correlation coefficients are achieved provided a smoothing kernel with a large enough bandwidth is used. The optimal cases are those with a high correlation coefficient and a short bandwidth. The case of early wood tree-ring width and yearly rainfall with an optimal bandwidth of 38 is shown in Fig. 5A. With respect to temperature, Fig. 5B shows the correlation coefficient between mean wood density and mean annual temperature as a function of the bandwidth that defines the amount of smoothing; the maximum correlation coefficient is -0.975 (Table 2).

For rainfall, the smoothed time series is given in Fig. 6A and the linear relationship between both is given in Fig. 6B. Both time series (Fig. 6A) show a similar pattern with a minimum annual rainfall between 1920 and 1950 when the tree rings have minimum widths. The linear relationship in Fig. 6B is statistically significant with a very low p-value, with relatively low dispersion around the straight line and a relatively high coefficient of determination.

For temperature, Fig. 7A shows the smoothed time series for mean wood density and for mean annual temperature for the maximum correlation coefficient of -0.975. Both time series in Fig. 7A show similar patterns with a clear linear trend of increasing temperature and decreasing mean wood density. The linear relationship between mean annual temperature and mean wood density is evident in Fig. 7B. The linear regression in Fig. 7B is statistically significant with a very low p-

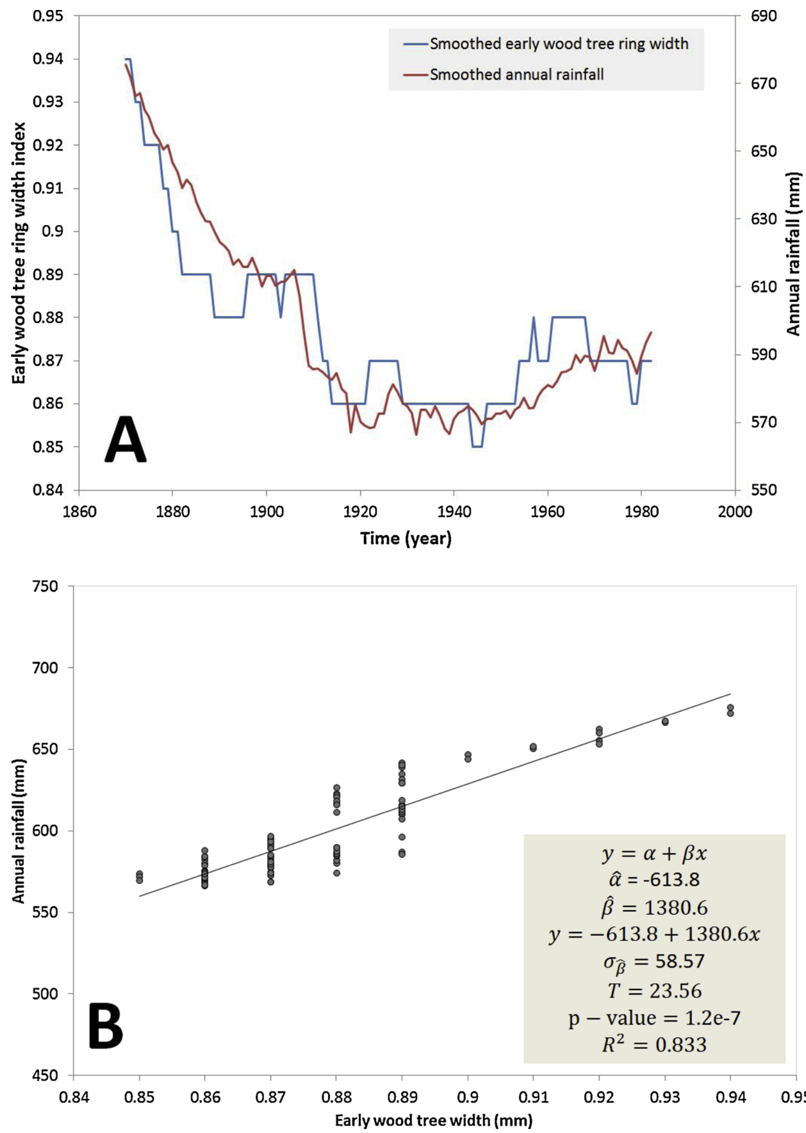


Fig. 6. Reconstruction of temperature. A: Smoothed time series for the maximum achieved correlation coefficient in Fig. 5. B: linear regression between the smoothed tree-ring and climate time series in A. The figure shows the estimates of the regression parameters: intercept (α) and slope (β), the standard deviation of the estimate of slope, the t-statistic, the p-value, and the coefficient of determination R^2. The low p-value (< 0.01) indicates the statistical significance of the linear relationship.

value, with relatively little dispersion around the straight line and a high coefficient of determination.

Some significant additional information was obtained by applying moving window running means to the complete 1728–1982 early wood time series (Fig. 8A). The running means in Fig. 8A show that the early wood tree-ring width decreased from 1728 to 1920, reached a minimum and stabilised over the period 1920 to 1950, and then began to increase. Applying the linear relationship in Fig. 6B to the smoothed time series in Fig. 8A, gives the time series shown in Fig. 9A. It should be noted that in Fig. 9A, the inferred past rainfall is not yearly rainfall but the smoothed yearly rainfall within a semi-bandwidth of 38 years. In other words, we are making inferences about the rainfall trend rather than the individual yearly rainfall, which is probably impossible to estimate with any acceptable measure of accuracy.

The same for temperature; additional significant information is obtained by applying moving window running means to the complete 1728–1982 mean wood density time series (Fig. 8B). There is a systematic decrease in mean wood tree ring density from 1728 to 1982. Applying the linear relationship in Fig. 7B to the smoothed time series in Fig. 8B generates the time series shown in Fig. 9B. It should be noted again that in Fig. 9B, the past temperature inference is not mean annual temperature but the smoothed mean annual temperature with a semi-bandwidth of 44 years. In other words, we are making inferences about the trend of the mean annual temperature. It is clear from this analysis that the temperature has been increasing with two changes of slope and faster increases in 1772 and in 1900. It should be noted that the results reported here refer to a particular location. The results will be different for averages over larger areas with a smoothing of local temporal

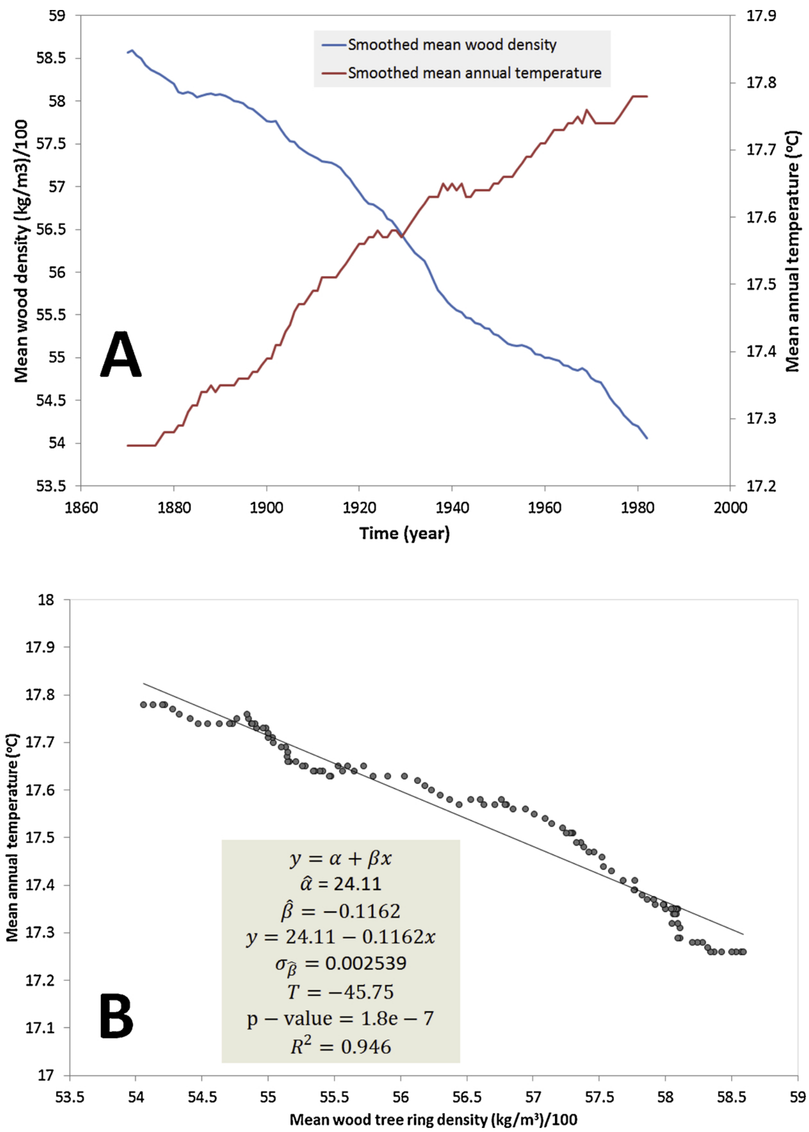


Fig. 7. A: Smoothed time series for the maximum achieved correlation coefficient in Fig. 9. B: linear regression between the smoothed tree-ring and climate time series in A. The figure shows the estimates of the regression parameters: intercept (α) and slope (β), the standard deviation of the estimate of slope, the t-statistic, the p-value, and the coefficient of determination R^2. The low p-value (< 0.01) indicates the statistical significance of the linear relationship.

variations in temperature. Thus, the particular values given here are not comparable with those reported by other authors for the whole of the northern hemisphere (Mann and Bradley, 1999), although the general trends are compatible.

These observations for the annual rainfall and the mean annual temperature at San Fernando station can be extrapolated to the study area in Sierra de las Nieves. This is because there is a good linear correlation between values recorded at the San Fernando stations and those recorded at stations in the study area (Sierra de las Nieves). This relationship was obtained by calculating mean time series of rainfall and temperature for the stations around the Sierra de las Nieves but which have data for the last decades only. The major differences between the San Fernando and the Sierra de las Nieves time series are that mean annual rainfall in the study area is 513 mm higher than at San Fernando and the variance is almost four times larger (Fig. 10A); the mean temperature is 7 °C lower in the study area than at San Fernando station but the variance in temperature is almost one-third less than the temperature at San Fernando station (Fig. 11A). Particular time series of annual rainfall and temperature can readily be obtained from a stochastic weather generator using the means and variances. However, this is outside the scope of the present work. Figs. 10B and 11 B show the statistically significant (very low p-value) relationships between the rainfall and temperature at San Fernando station and Sierra de las Nieves with differences due to the difference in altitude.

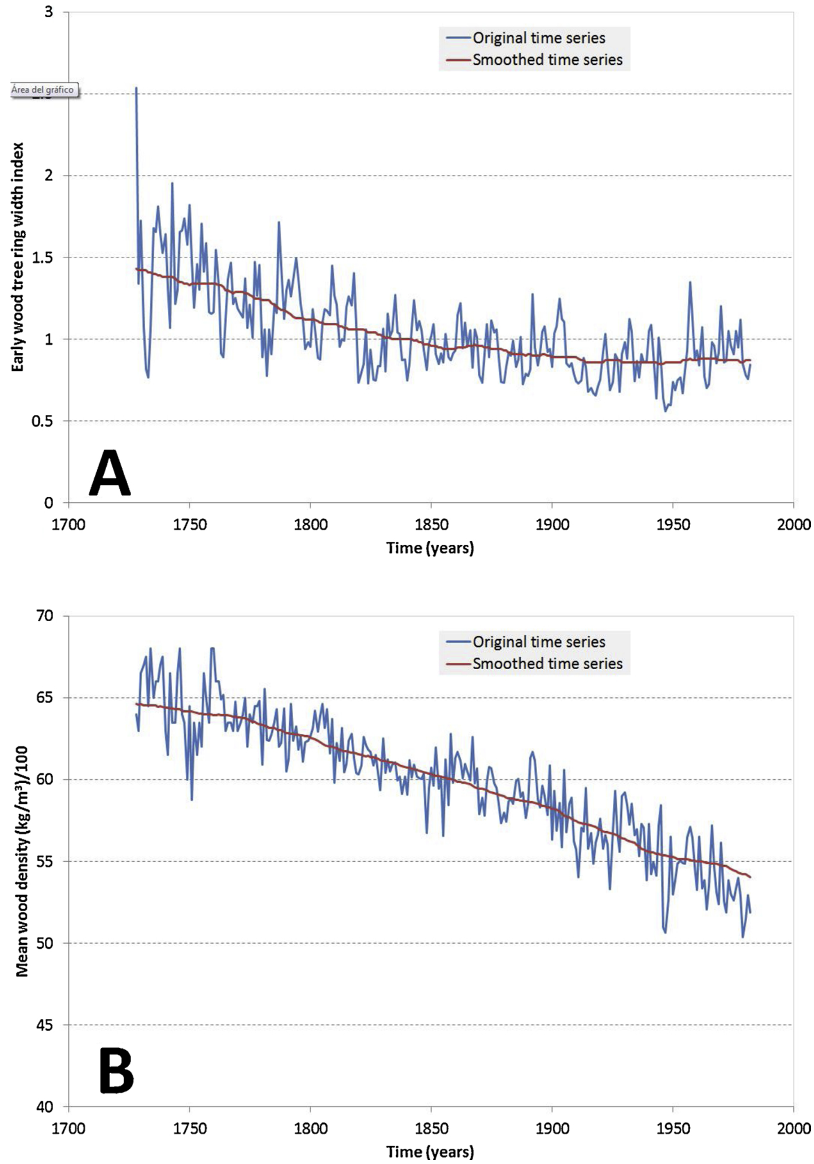
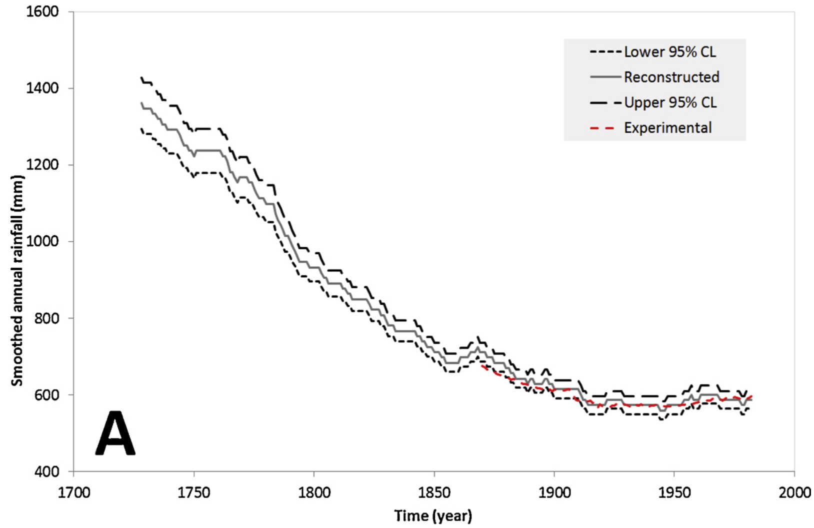


Fig. 8. A: Original early wood tree-ring width index and moving average trend for the period 1728–1982. The semi-bandwidth (44 years) that maximises the correlation with yearly rainfall has been used. B: Original mean tree-ring wood density and moving average trend for the period 1728–1982. The semi-bandwidth (48 years) that maximises the correlation with mean annual temperature has been used.

4. Discussion

For the purpose of illustrating the methodology presented here we have used only the early wood tree-ring width, mean tree-ring wood density, annual rainfall and mean annual temperature. However, in practice, all combinations of tree and climate variables can be included depending on the purpose of the study. For example, if winter rainfall and mean spring temperature are variables of interest, they could be derived from appropriate correlated tree-ring variables. In the work presented here we have used early wood tree-ring width to infer past trends in rainfall and mean tree-ring wood density to infer past trends in mean temperature. Rainfall and temperature influence tree-ring variables but not in the same way and they are not the only climate variables that influence tree-ring variables. The results for the mean reconstructed averages of yearly rainfall and mean yearly temperature show that rainfall has been decreasing since 1728 (the lower time limit imposed by the tree-ring data) to a minimum around 1930 and since then it has been increasing to the levels of the 19th century. There has been an increase in temperature since 1728 with a greater rate of increase in 1772 and around 1900.

Perhaps the most difficult part of a paleoclimatic reconstruction is the validation of the results. With respect to temperature, the trend of our reconstruction is consistent with the results of Mann and Bradley (1999) as represented in Fig. 12A - keeping in mind that we are



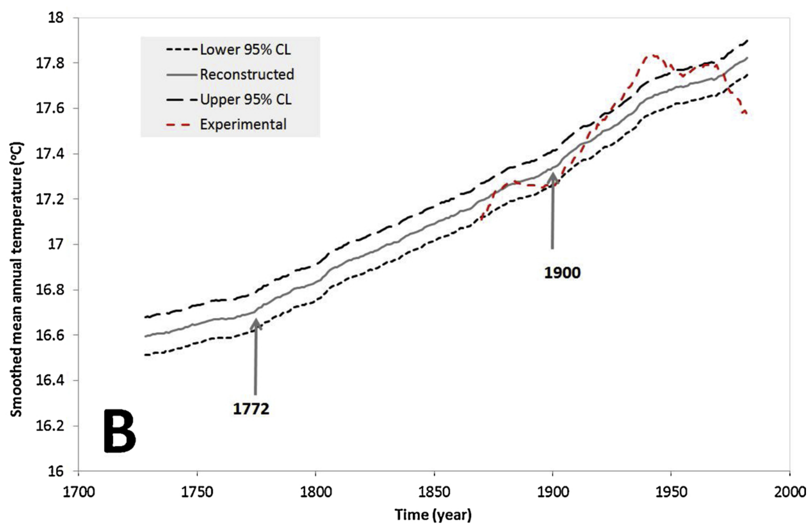
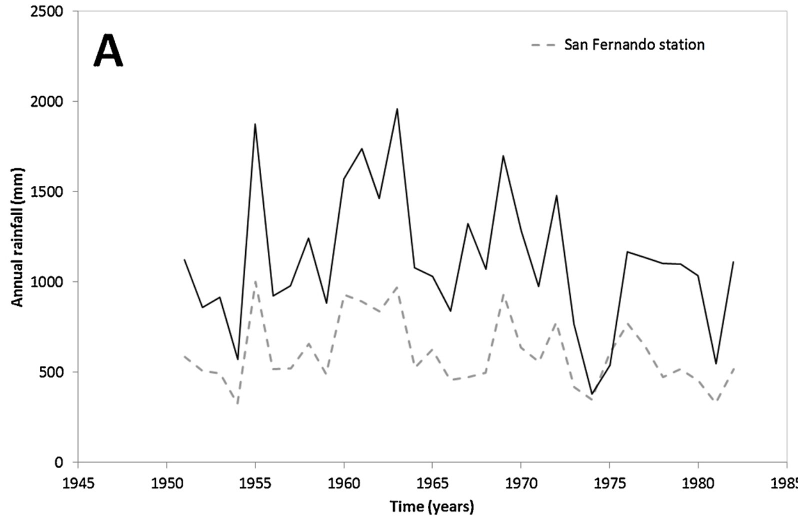


Fig. 9. A: Linear reconstruction of the trend of yearly rainfall for the period 1728–1982 using standard linear regression. The dashed line represents the experimental values for the calibration period. B: Linear reconstruction of the trend of mean annual temperature for the period 1728–1982 using standard linear regression. The dashed line represents the experimental values for the calibration period.

performing the reconstruction at a particular location while Mann and Bradley (1999) give trends for the entire northern hemisphere. With respect to rainfall, Rodrigo (2007) reconstructed flooding at Seville from documental records. Fig. 12B shows a moving average for the period covered in Rodrigo (2007) from which it can be seen that the results are consistent with higher rainfall in the past and a decrease until the beginning of the 20th century.

5. Conclusions

The work presented here addresses the problem of climate modelling and prediction when there are very few instrumental measurements of climate variables and it is thus not possible to reconstruct exact time series. A statistical approach is proposed for cases in which there is a complex relationship between climate variability and tree-ring features for a particular period and a specific location. The procedure has been demonstrated by application to the Sierra de las Nieves karst aquifer, a high-relief Mediterranean karst area in which there are complex climate relationships, but instrumental data are scarce. This problem has been addressed by statistical analysis of tree-ring data from *Abies Pinsapo*. These data were used to evaluate current climate variability (trends) of rainfall and temperature and the manner in which the climate has evolved from the past. The correlation between instrumental and proxy variables is complex and only revealed when a large averaging is applied to the available data to extract correlations and trends from those data. In the proposed methodology, time series are smoothed by a moving window running mean for which the bandwidths are chosen so as to maximise the absolute value of the correlation coefficient between the resulting tree-ring, and climate, time series. Although better results could be obtained with longer time



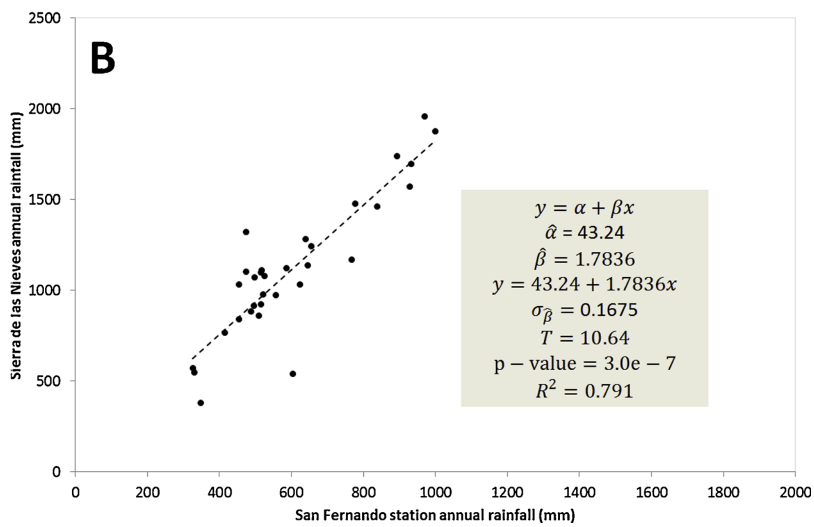
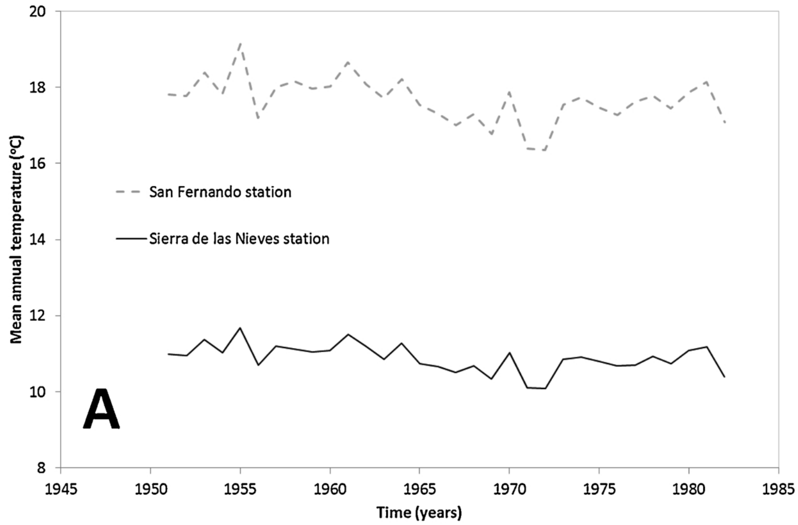


Fig. 10. A. Reconstruction of rainfall at Sierra de las Nieves from the correlation between nearby meteorological stations and San Fernando station. B: linear regression used in the reconstruction. The figure shows the estimates of the regression parameters: intercept (α) and slope (β), the standard deviation of the estimate of slope, the t-statistic, the p-value, and the coefficient of determination R^2. The low p-value (< 0.01) indicates the statistical significance of the linear relationship.



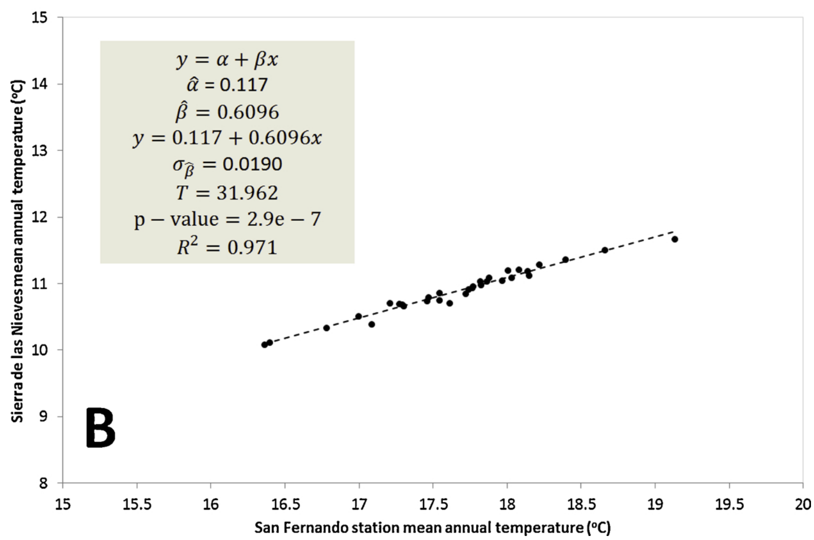


Fig. 11. A. Reconstruction of temperature at Sierra de las Nieves from the correlation between nearby meteorological stations and San Fernando station. B: linear regression used in the reconstruction. The figure shows the estimates of the regression parameters: intercept (α) and slope (β), the standard deviation of the estimate of slope, the t-statistic, the p-value, and the coefficient of determination R^2. The low p-value (< 0.01) indicates the statistical significance of the linear relationship.

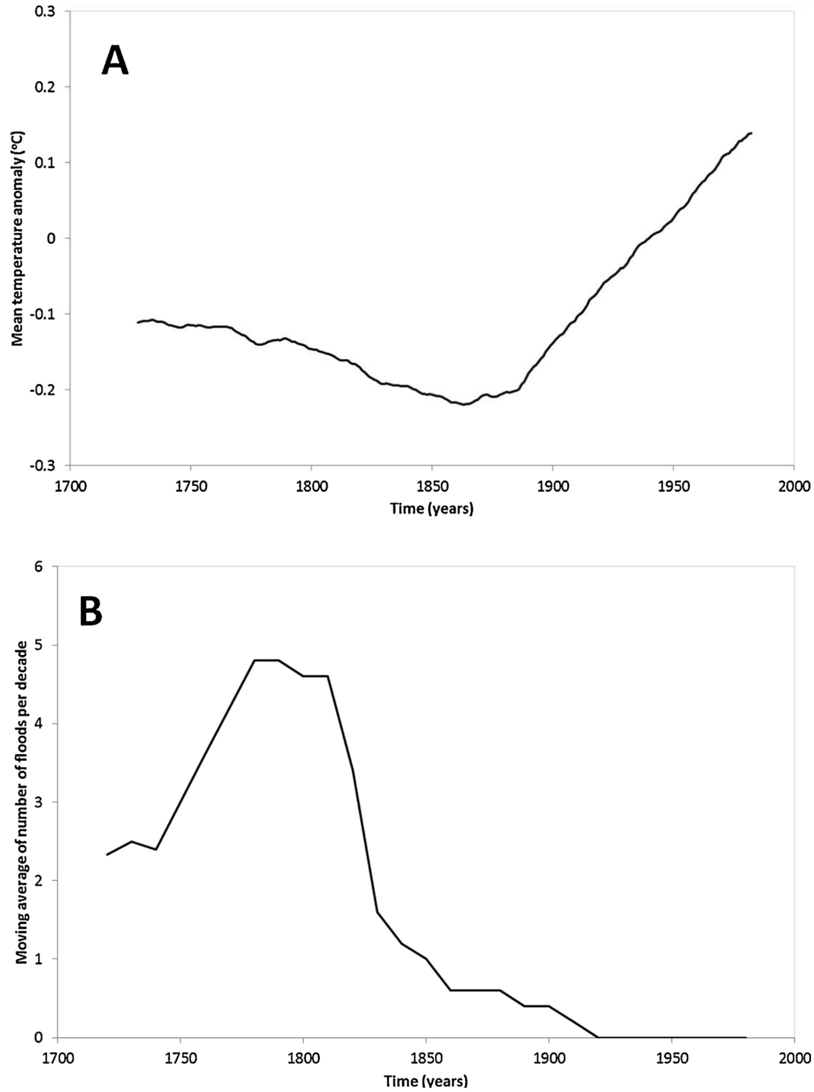


Fig. 12. A. Trend of northern hemisphere temperature modified from Mann and Bradley (1999). B. Trend of flooding in the Guadalquivir River in Seville modified from Rodrigo (2007).a.

series, any inference about past climate is a useful contribution to the assessment of current climate variability.

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